Justice behind coal-to-clean: Geospatial modeling of Medicaid dynamics in coal-dependent regions in Appalachia of the United States

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Abstract

The United State coal-to-clean transition has imposed concentrated economic shocks on coal-dependent regions, with potential implications for Medicaid pressure. This paper examines how poverty-based Medicaid pressure evolved across Appalachian counties from 2009–2019 and whether coal-reliant areas experienced differential changes after the 2015 policy-period break-point. Using a panel of 423 Appalachian counties, we document strong spatial clustering and persistent spatial dependence. Spatial models show that higher unemployment and lower educational attainment are robust correlates of Medicaid pressure, with evidence of spillovers from neighboring counties. An event study around the 2015 Clean Power Plan shows no detectable pre-trends and a positive post-2015 divergence in poverty-based Medicaid pressure between coal-reliant and non-coal counties. Importantly, spatial difference-in-differences estimates indicate that the post-2015 divergence is explained mainly by exposure to nearby coal-reliant counties, rather than by changes confined to coal-reliant counties themselves. These results suggest that Medicaid demand pressure is a regional phenomenon that can extend beyond coal counties through cross-county linkages. "Just transition" strategies should therefore coordinate labor-market stabilization and economic diversification with health-coverage and safety-net planning at a regional scale.

Keywords: Just transition; Spatial spillovers; Spatial DID; Coal dependence; Poverty-based Medicaid pressure; Appalachia

1 Introduction

Over the past decade, the United States has experienced a profound energy transition. U.S. coal production declined from 1.07 billion short tons in 2009 to 706 million short tons in 2019, representing a 34% decrease (U.S. Energy Information Administration, 2010, 2021). In contrast, dry natural gas production rose from 21.7 trillion to 34.0 trillion cubic feet, a 57% increase (U.S. Energy Information Administration, 2025c). This transition has been driven in part by de-carbonization policies that incentivize cleaner energy sources (Duenas-Martinez, Tapia-Ahumada, Hodge, Miller, & Parsons., 2021). However, the rapid energy transition has imposed substantial costs on coal-reliant regions, including job losses, business closures, and shrinking local tax bases that increase poverty and expand reliance on Medicaid, adding further economic and social burdens (Blonz, Roth Tran, & Troland, 2023; Bowen, Christiadi, Deskins, & Lego, 2021a; Hanson, 2023).

Appalachia is one of the major coal-producing regions in the United States. According to the Appalachian Regional Commission (ARC), the region consists of 423 counties in 13 states, from southern New York to northern Mississippi (2025). From 2001 to 2021, approximately 57.7% of national coal production came from 153 coal-producing counties within Appalachia (U.S. Energy Information Administration, 2025a). Following the implementation of major federal de-carbonization and clean-energy policy initiatives in 2015, annual coal output in Appalachia fell by 26.1% from 2009 to 2019. This sharp contraction has made the region particularly vulnerable during the ongoing energy transition.

During this same period, reliance on Medicaid—the public insurance program that provides health coverage for low-income individuals—grew more rapidly, placing increasing pressure on local healthcare safety nets. Although Medicaid pressure has been widely influenced by national policy reforms, the disproportionate growth observed in coal-reliant Appalachian counties raises questions about the role of region-specific economic shocks. In particular, Medicaid enrollment population in the 13 Appalachian states increased from roughly 20.4 million to 28.1 million from fiscal year 2009 to fiscal year 2019, a 38.1% increase compared with 30.8% growth in non-Appalachian states (Medicaid and CHIP Payment and Access Commission, 2012, 2021).

Previous research has examined broader implications of de-carbonization policies for local vulnerable communities, including economic shocks, employment displacement, and regional disparities in health and environmental outcomes (Greenberg, 2018; Michieka, Graziano, Musso, & Fouquet, 2022; Sovacool, Martiskainen, Hook, et al., 2019). However, the specific mechanisms through which coal production decline shapes Medicaid pressure remain insufficiently understood. Moreover, little empirical work has clarified whether Medicaid pressure in coal-producing regions is primarily driven by structural economic decline, policy reforms, or demographic changes. To fill this gap, this study seeks to answer two research questions: *(1) What local conditions and neighboring spillovers are associated with changes in Medicaid pressure across Appalachian counties during 2009–2019? (2) To what extent have federal de-carbonization policies contributed to the divergence in Medicaid pressure between coal-reliant and non-coal counties?* Answering these questions is essential for understanding how large-scale

energy transitions reshape social safety-net programs in resource-reliant regions. This work contributes to ongoing national discussions around a "just transition", particularly as federal initiatives increasingly emphasize clean-energy development paired with equitable economic restructuring.

This paper contributes to the literature in several ways. First, to our knowledge, it is the first quantitative, county-level geospatial study to examine how coal dependence, local socioeconomic conditions, and environmental risk factors jointly shape Medicaid pressure across Appalachian during the coal-to-clean energy transition. Second, we measure Medicaid pressure using "poverty-based Medicaid pressure" (county poverty rate) due to incomplete enrollment data and validate it where coverage data are available. Third, we explicitly model cross-county dependence by estimating spatial panel specifications and a spatial Difference-in-Differences (Spatial-DID) design that separates direct exposure from neighbor exposure, allowing us to quantify spillovers. Fifth, the analysis uses a rich dataset from the U.S. Energy Information Administration (2020a), the Appalachian Regional Commission (2021), and the U.S. Centers for Disease Control and Prevention (2010; 2011; 2019), integrating information on coal production, environmental pollutants, and socioeconomic indicators. Together, these elements offer a novel empirical framework for understanding how large-scale energy transitions reshape Medicaid pressure and the broader social safety net in coal-reliant regions, with direct implications for designing regionally tailored "just transition" policies.

Our results based on spatial lag models show that unemployment, educational attainment, and exposure to hazardous air pollutants (HAPs) are strongly associated with poverty-based Medicaid pressure. The DID model shows post-policy divergence between coal-reliant and non-coal counties, with no detectable pre-trends. Extending the design to a spatial-DID framework further suggests that the post-policy divergence is driven primarily by neighbor exposure rather than changes confined to coal-reliant counties themselves. Taken together, the results imply that transition-related safety-net pressure is regional in nature and motivate "just transition" policies that coordinate decarbonization with labor-market support and safety-net planning, particularly in high-burden subregions.

2 Literature Review

In 2015, the United States Environmental Protection Agency introduced the Clean Power Plan, a national regulatory framework that set the first nationwide limits on carbon dioxide emissions from existing power plants (2015). Subsequently, in 2021, the United States strengthened its climate stance by committing to reach net-zero emissions by 2050 (The White House, 2021). These commitments imply an energy transition that goes beyond a simple technological shift from fossil fuels to low-carbon energy sources; they also require a deep economic and social transformation aimed at reinforcing the national economy while advancing equity and inclusion (National Academies of Sciences, Engineering, and Medicine, 2021). Within the broader fossil fuel sector, the coal industry and coal-dependent communities have experienced particularly severe adjustment pressures, including employment losses, shrinking local

tax bases, and rising social vulnerability. In this context, a growing coalition of labor organizations, environmental justice groups, and policy scholars has argued that the low-carbon transition must be a "just transition"—one that directly mitigates the harms experienced by workers and communities reliant on fossil fuels, rather than treating these harms as unavoidable side effects of decarbonization (Carley & Konisky, 2020; Henry, Bazilian, & Markuson, 2020; Sovacool, Furszyfer Del Rio, & Griffiths, 2020). This perspective highlights that assessments of energy transition policies must consider not only emissions, but also the role of social protection in supporting vulnerable households in coal-reliant regions.

Existing studies suggest several mechanisms through which coal dependence and associated economic shocks can increase Medicaid pressure. First, economic distress raises the number of uninsured. Coal mine closures and contractions in related industries lead to substantial job loss, resulting in the loss of benefits such as employer-sponsored insurance; in these circumstances, Medicaid acts as a countercyclical safety net, leading to increases in enrollment (Krause, 2023). Persistent poverty in many Appalachian coal-reliant counties—characterized by low incomes, lower educational attainment, and limited economic diversification—further constrains households' ability to afford commercial coverage leading to greater reliance on public health insurance (Lobao, Partridge, Jiang, & Hooks, 2016). Second, elevated rates of chronic obstructive pulmonary disease (COPD) in coal-reliant regions can also function as gateways to Medicaid eligibility. Studies note that populations living in Central Appalachia are disproportionately affected by lung disease, driven in part by occupational hazards and environmental exposures, as respirable coal and silica dust have toxic effects on coal miners (DeBolt, Brizendine, Tomann, & Harris, 2021). Moreover, research shows that coal-reliant regions continued to experience high levels of illness and mortality during the COVID-19 pandemic (Van Slyke, 2020), indicating that the health burden in these communities persists and underscoring the need to identify the most vulnerable regions during the transition.

Beyond coal-specific mechanisms, prior work emphasizes that Medicaid enrollment exhibits substantial geographic variation. On one hand, Medicaid eligibility differs by state. Under the Patient Protection and Affordable Care Act (PPACA), Medicaid eligibility was expanded beginning in 2014 to cover all low-income adults up to 138% of the Federal Poverty Level (FPL). However, the 2012 Supreme Court decision made Medicaid expansion optional for states. In other words, "Medicaid expansion states" extend coverage to nearly all adults below 138% of the FPL, whereas "non-expansion states" retain more restrictive eligibility rules and thus narrower enrollment. As of September 2025, ten states have not adopted the expansion; among them, Alabama, Georgia, Mississippi, and Tennessee contain counties designated as part of the Appalachian region (KFF, 2026). This implies that Appalachian counties in these states operate under more restrictive Medicaid eligibility rules than comparable counties in expansion states, which shape observed enrollment patterns and health outcomes (Romero & Ponomariov, 2023). On the other hand, geographic heterogeneity within Appalachia further implies that Medicaid dynamics differ across subregions: coal industry employment shocks are spatially concentrated, with the most coal-dependent counties disproportionately located in Central Appalachia, a subregion that

also exhibits higher poverty and weaker socioeconomic indicators than Northern and Southern Appalachia (Bowen, Christiadi, Deskins, & Lego, 2021b; Lichter & Campbell, 2005). Moreover, evidence from a rural–urban analysis of Medicaid enrollment changes finds that Medicaid growth is uneven and is generally lower in rural counties (Barker, Huntzberry, McBride, & Mueller, 2016). Together, these findings suggest that Medicaid enrollment changes exhibit substantial geographic variation, motivating an empirical approach that explicitly models spatial dependence.

Prior quantitative research linking energy-transition shocks to local socioeconomic and health outcomes generally follows two empirical approaches: difference-in-differences (DID) policy evaluation and spatial econometric modeling. For example, Mark et al. combine two-way fixed effects with spatial econometric models on county panel data to test whether coal mine closures generate spillovers, finding an immediate rise in unemployment with spatial "ripple" effects into neighboring counties (2024). Greenberg similarly uses spatial regression with Queen contiguity to capture spatial dependence, showing that closer proximity to coal-waste impoundments is associated with larger poverty increases over time (2018). Lee et al. use a staggered roll-out DID design to credibly evaluate policy timing, finding that China's coal-to-clean heating policy reduced acute myocardial infarction incidence in exposed townships relative to non-exposed townships (2024). Despite these contributions, each approach has limitations. DID designs can be biased when outcomes exhibit strong spatial dependence or cross-border spillovers (Hudgens & Halloran, 2008). These conditions are likely in Appalachia given integrated labor markets, healthcare access, and migration, which can weaken the no-interference intuition. Spatial models explicitly capture spatial autocorrelation and quantify neighbor effects, but without an external shock they often remain primarily associational and can be sensitive to omitted time-varying confounders and the choice of spatial weights (Stakhovych & Bijmolt, 2009). These limitations motivate hybrid spatial Difference-in-Difference (spatial–DID) frameworks that combine policy-shock identification with explicit modeling of spatial dependence, enabling estimation of both direct local impacts and indirect spillover effects.

3 Study Area, Data, and Pre-processing

3.1 Study Area

We follow the Appalachian Regional Commission (ARC) definition of Appalachia, which encompasses 423 counties across 13 U.S. states. Within this ARC-defined boundary, we use the U.S. Energy Information Administration's (EIA) coal-producing regions to distinguish three coal subregions: Northern, Central, and Southern. In addition, we classify individual counties as "coal counties" or "non–coal counties" using the EIA's operational definition: a county is defined as a coal county if it recorded at least 1,000 short tons of coal output in any year between 2000 and 2022 (2025b). Coal production has evolved very differently across these subregions. Over the past two decades, the sharpest contraction has occurred in Central Appalachia, where output fell by more than 78%, from over 270 million short tons in 2001 to under 60 million short tons in 2022. In contrast, Northern Appalachia experienced a more moderate decline of about 36%, while Southern Appalachia has remained a comparatively small

producer with low levels of output (U.S. Energy Information Administration, 2025a). Alongside coal's decline, parts of Northern Appalachia have seen rapid growth in natural-gas production (U.S. Energy Information Administration, 2025d), illustrating a shift from coal toward cleaner fossil fuels . Taken together, the uneven production declines across coal subregions, Appalachia's long-standing socioeconomic vulnerabilities, and Northern Appalachia's substantial natural-gas output highlight the region's central role in the coal-to-clean transition and make it an ideal setting for our analysis of Medicaid dynamics and distributional justice in the coal-to-clean transition.

3.2 Data Sources

We construct a county-level panel for the period 2009–2019 for all counties in the ARC-defined Appalachian region. All datasets are harmonized to a common county–year structure using Federal Information Processing Standards (FIPS) codes as the primary geographic identifier. When source data are reported at different geographic resolutions or temporal frequencies, we align them to the county–year unit using standard crosswalks and document any interpolation or aggregation procedures in Section 4.3.

Outcome (Poverty-based Medicaid pressure). Our preferred outcome is the county-level Medicaid coverage rate, but a consistent county–year enrollment series is not available for the full study period, especially in earlier years from 2009 to 2014. We therefore construct poverty-based Medicaid pressure, defined as the county poverty rate, and interpret it as an indicator of Medicaid pressure. This choice is motivated by the fact that Medicaid eligibility is income-tested and tied to Federal Poverty Level thresholds, so poverty captures the size of the low-income population most likely to rely on Medicaid. To assess construct validity, we perform a correlation analysis and fixed-effects validation in Appendix Tables A.1–A.2 using ACS county estimates of Medicaid coverage rate (Medicaid/means-tested public coverage, Subject Table S2704) (U.S. Census Bureau, 2019b) and poverty rate (percent below poverty level, Subject Table S1701) (U.S. Census Bureau, 2019a) for 2015–2019, showing a strong positive relationship both nationally and within Appalachia.

Coal dependence. County coal production is measured using U.S. Energy Information Administration (EIA) data on coal output, measured in thousand short tons at the county level (2020b).

Socioeconomic conditions. County-level socioeconomic covariates—including the unemployment rate (percent of the labor force unemployed and seeking work), educational attainment (percent of high school and college completion rates), and population—are obtained from the Appalachian Regional Commission (ARC) Data Reports (2023).

Environmental risks. We measure ambient air exposures using three CDC Environmental Public Health Tracking products. First, $PM_{2.5}$ (Estimated Avg. 24-hr $PM_{2.5}$ in $\mu g/m^3$) and ozone (Estimated Avg. 8-hr ozone concentration in ppb) are obtained from the CDC: Air Daily Census Tract-Level $PM_{2.5}$/Ozone Concentrations. Hazardous air pollutants (HAP)—benzene, formaldehyde, acetaldehyde, carbon tetrachloride, and 1,3-butadiene—are obtained from the CDC: Annual Average Cancer Risk Estimates and are measured as lifetime cancer risk per one million people ("N-in-1 million"). All environmental indicators are standardized to county–year units; where

pollutant series are not observed annually for all counties, we apply linear interpolation as described in Section 4.3.

Spatial weights matrix. To model spatial dependence and spillovers across counties, we construct a county-level spatial weights matrix W based on Queen contiguity, using county boundary polygons from the Opendatasoft: U.S. County Boundaries GeoJSON dataset (U.S. Census Bureau, 2017). We row-standardize W so that each county's neighbor weights sum to one and use this matrix to compute spatial lags (e.g., $(WY)_{it}$ and $(WX)_{it}$) in the spatial panel regressions.

3.3 Data Processing and Transformation

All data processing and transformations are implemented in Python. Several hazardous air pollutants (HAPs) are reported only for certain years (e.g., 2011, 2014, and 2017–2019). Because our spatial panel models require a complete county–year panel, we impute missing years using linear interpolation based only on each county's nearest available years. This follows the imputation strategy described by Moritz and Bartz-Beielstein (2017). Coal output is measured in short tons and converted to coal production per capita (short tons per person) by dividing county coal production by county population. Population density is calculated as county population divided by county land area (persons per square mile). To improve model fit, we apply log transformations to right-skewed continuous measures such as population density (*PopDens*) and coal output (*CoalDepend*). To mitigate multicollinearity among hazardous air pollutant measures, we construct a single composite HAP index (*HAP*) by averaging pollutant-specific lifetime cancer-risk estimates (formaldehyde, 1,3-butadiene, benzene, naphthalene, and acetaldehyde).

4 Methodology

Using the data described in Section 4, we estimate panel models to examine how Medicaid pressure evolves across Appalachian counties and whether the post-2015 policy period—marked by the release of the Clean Power Plan (CPP)—is associated with differential changes in coal-reliant counties.

First, we test whether Medicaid pressure exhibits spatial dependence across counties. Second, we implement a policy-focused difference-in-differences (DID) design that uses 2015 as a breakpoint to assess whether coal-reliant counties experienced a larger post-policy increase in poverty-based Medicaid pressure. Third, we integrate these two components by extending the DID framework to a spatial-DID specification that explicitly accounts for spatial spillovers

4.1 Spatial dependence

We define spatial neighbors using a row-standardized Queen contiguity weight matrix W based on shared county boundaries. To assess whether spatial dependence remains after removing county and year effects, we first estimate a two-way fixed effects (TWFE) model for poverty-based Medicaid pressure with the full set of controls, and

then compute Global Moran's I on the TWFE residuals for each year. Statistical significance is evaluated using a permutation test based on 999 permutations.

4.2 Spatial panel models

To characterize the sources of spatial dependence, we estimate spatial fixed-effects panel models using the same weights matrix W. Our preferred specification is the spatial Durbin model (SDM):

$$Y_{it} = \rho(WY)_{it} + X_{it}\gamma + (WX)_{it}\theta + \alpha_i + \lambda_t + \varepsilon_{it}. \tag{1}$$

where Y_{it} denotes poverty-based Medicaid pressure for county i in year t; X_{it} is a vector of time-varying controls; α_i and λ_t are county and year fixed effects; $(WY)_{it}$ is the spatial lag of the outcome; and $(WX)_{it}$ is a vector of spatially lagged covariates. Parameter ρ captures the strength of outcome dependence across neighbors. We compare model fit across the spatial autoregressive model (SAR), spatial error model (SEM), and SDM using AIC/BIC and log-likelihood, and we check residual spatial autocorrelation.

4.3 Baseline DID: TWFE-DID and Event-study

To link poverty dynamics to a major federal de-carbonization policy period, we use 2015 as a breakpoint and estimate a two-way fixed effects difference-in-differences (TWFE-DID) model:

$$Y_{it} = \alpha_i + \lambda_t + \beta D_{it} + \mathbf{X}_{it}\gamma + \varepsilon_{it}, \tag{2}$$

$$D_{it} = \text{Treated}_i \times \text{Post2015}_t. \tag{3}$$

Where $\text{Treated}_i = 1$ for coal-reliant counties (top quartile of CoalBase_i), 0 otherwise; $\text{Post2015}_t = 1$ for years 2015–2019, 0 for years 2009–2014; D_{it} is direct treatment exposure; β is treated–control change after 2015.

Treatment is defined using a predetermined baseline measure of coal reliance:

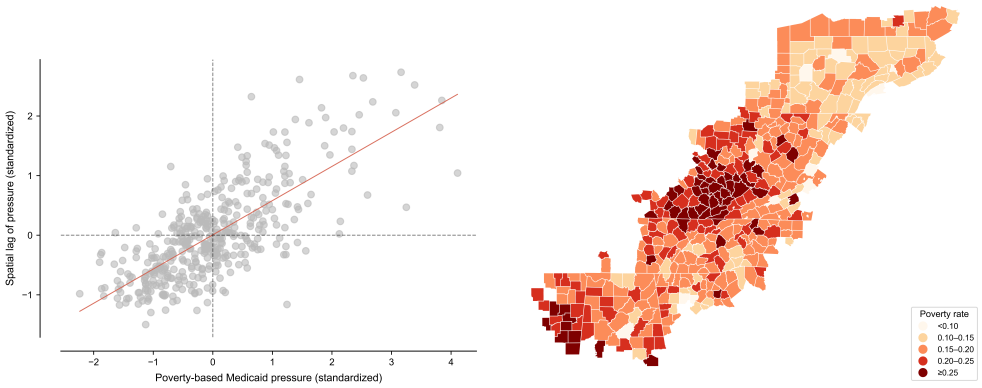
$$\text{CoalBase}_i = \frac{1}{6}\sum_{t=2009}^{2014} \text{CoalDepend}_{it}. \tag{4}$$

Where CoalDepend_{it} is logged coal production per capita.

To assess pre-trends and dynamic effects, we estimate an event-study specification that omits 2014 (k=-1) as the reference year:

$$Y_{it} = \alpha_i + \lambda_t + \sum_{k\neq -1} \beta_k \left(\text{Treated}_i \times 1[\text{event_time}_t = k]\right) + \mathbf{X}_{it}\gamma + \varepsilon_{it}. \tag{5}$$

Where β_k is the event-study coefficient capturing treated–control differences at event time k.



(a) (b)

Fig. 1 Spatial distribution of poverty-based Medicaid pressure changes and neighbor exposure. (a) Moran's I scatterplot (2014). (b) Poverty map (2014).

4.4 Spatial dependence and spillovers: Spatial-DID

The baseline DID captures differential post-2015 changes in treated counties but implicitly assumes that counties are independent units. In Appalachia, counties are highly interconnected through labor markets, commuting flows, population mobility, healthcare access, and environmental exposure, so a policy shock affecting coal-reliant counties may also spill over to nearby non-treated counties. To account for such spillovers, we follow the Spatial-DID framework of Chagas et al., which augments DID by incorporating spatial exposure to treated neighbors (2016). Accordingly, we estimate:

$$Y_{it} = \alpha_i + \gamma_t + \beta D_{it} + \Phi(WD)_{it} + \mathbf{X}_{it}\gamma + \varepsilon_{it}, \qquad (WD)_{it} \equiv \sum_j w_{ij} D_{jt}. \quad (6)$$

Where $(WD)_{it}$ is exposure to treated neighbors; Φ is spillover effect associated with higher neighbor treatment exposure.

5 Result

5.1 Descriptive spatial patterns

Figure 1 shows that Poverty-based Medicaid pressure exhibits clear spatial clustering across Appalachia. We illustrate this pattern using a representative mid-sample year (2014). The Moran scatterplot in Figure 1(a) indicates a positive association between a county's pressure and the average pressure of its neighbors, with substantial mass in the high–high and low–low quadrants. Consistent with this visual evidence, spatial autocorrelation in 2014 is strong and statistically significant (Moran's I=0.574, expected I=-0.0024, p=0.001). The map in Figure 1(b) corroborates these patterns,

with high-pressure counties concentrated in Central Appalachia and South Appalachia, low-pressure counties concentrated in North Appalachia.

Spatial dependence also remains in the panel after accounting for county fixed effects, year fixed effects, and observed controls. Moran's I computed on TWFE residuals is positive in all 11 years and statistically significant in 9 of the 11 years, with the strongest residual clustering in 2012 ($I = 0.164$, $p = 0.001$). Year-specific residual diagnostics are reported in Appendix Table A.3. Together, the cross-sectional clustering and residual tests indicate meaningful spatial dependence, supporting the use of spatial panel and spatial-DID specifications in the subsequent analysis.

5.2 Spatial panel models

Table 1 SDM model details

Variable	SDM
$CoalDepend_{it}$	0.0001
Edu_{it}	-0.0287***
$Unemp_{it}$	0.1361***
$PopDens_{it}$	-0.0275***
$PM25_{it}$	0.0008
$Ozone_{it}$	0.0002
HAP_{it}	-0.0037**
$W\ CoalDepend_{it}$	-0.0025***
$W\ Unemp_{it}$	0.1587***
$W\ HAP_{it}$	0.0071***
$\rho\ (WY_{it})$	0.0985***

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We estimate three spatial fixed-effects panel models (SAR, SEM, and SDM) using the same spatial weights matrix. Model comparisons are reported in Appendix Table A.4. The SDM fits the data best, with the highest log-likelihood and the lowest AIC/BIC, and is therefore used as the main specification. Table 1 reports SDM estimates for poverty-based Medicaid pressure. Within counties over time, education is negatively associated with pressure, while unemployment is positively associated with higher pressure; population density is also negative and statistically significant, as is HAP exposure. Coal dependence is small and not statistically significant, and $PM_{2.5}$ and ozone are weakly related to the outcome in this specification.

Several spatially lagged covariates are statistically significant, including neighboring unemployment, neighboring HAP exposure, and neighboring coal dependence. This pattern is consistent with spatial spillovers: local pressure is related not only to a county's own characteristics but also to conditions in nearby counties. Coal dependence appears more relevant through neighboring exposure than through own-county exposure, as the local coal term is not significant whereas $W\ CoalDepend_{it}$ is. Finally, the

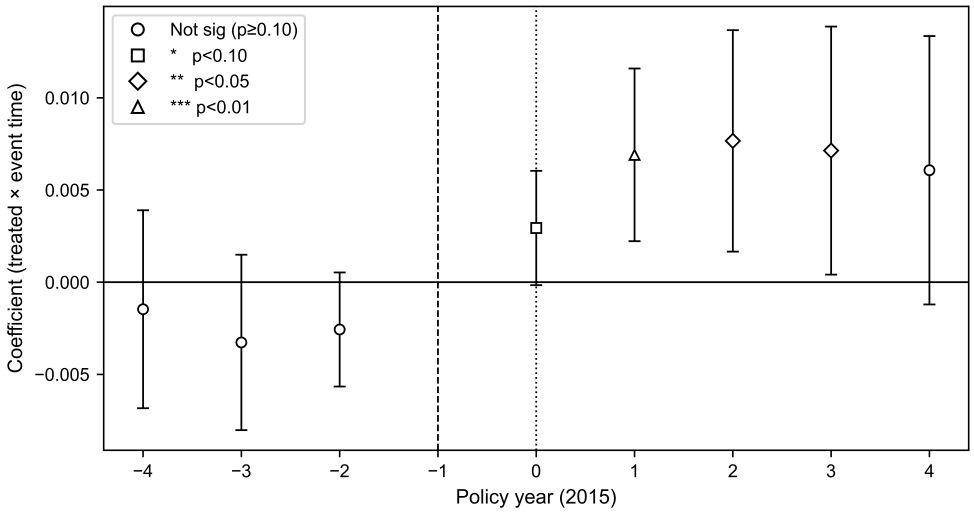


Fig. 2 TWFE event-study around the 2015 Clean Power Plan. Dots show the estimated difference between coal-reliant (treated) and non-coal (control) counties. Bars are 95% confidence intervals. The reference year is 2014 ($k = -1$).

spatial autoregressive parameter ρ is positive and significant, indicating that residual spatial dependence remains after control.

5.3 Baseline policy evidence

Figure 2 presents TWFE event-study estimates of the change in poverty-based Medicaid pressure for treated versus control counties, normalized to the year just before the policy ($k = -1$, 2014). The pre-policy coefficients are small and not statistically different from zero, with 95% confidence intervals that include zero. Consistent with this pattern, a joint Wald test fails to reject that the lead coefficients are jointly zero ($\chi^2 = 4.215$, $p = 0.239$), providing support for parallel trends over the immediate pre-policy period. After 2015 and the release of the Clean Power Plan, the estimates turn positive, indicating that poverty-based Medicaid pressure rises more in treated counties than in controls ("post-policy divergence" in the following). The contemporaneous estimate ($k = 0$) is positive and marginally significant, whereas the post-policy effects are statistically significant for $k = +1$ through $k = +3$. The estimate at $k = +4$ remains positive but is not statistically significant, suggesting that the post-policy divergence is concentrated in the first few years after the breakpoint.

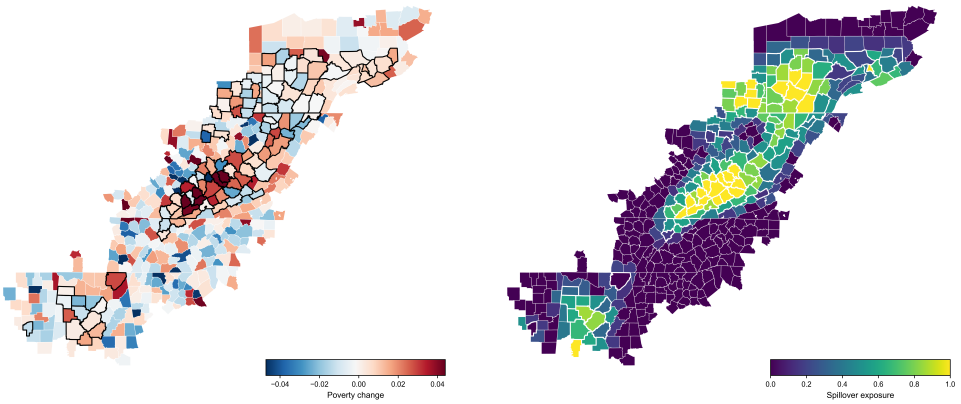
5.4 Spatial-DID: direct and neighbor exposure

Table 2 reports three specifications that separate post-2015 direct exposure (D) from neighbor exposure (WD). In the TWFE-DID specification (col. 1), direct exposure is positive and statistically significant ($D = 0.0073$, SE $= 0.0028$, $p < 0.01$), indicating a larger post-2015 increase in poverty-based Medicaid pressure in treated counties

Table 2 Spatial-DID Estimates of Poverty-based Medicaid Pressure (TWFE-DID, WD-only, and Spatial-DID)

Variables	(1) TWFE DID	(2) WD-only	(3) Spatial-DID
Treat × Post2015 (D)	0.0073*** (0.0028)	—	0.0008 (0.0030)
W·(Treat × Post2015) (WD)	—	0.0142*** (0.0046)	0.0135** (0.0055)
Education	-0.0317** (0.0152)	-0.0295* (0.0152)	-0.0297* (0.0152)
Unemployment	0.2407*** (0.0601)	0.2098*** (0.0616)	0.2093*** (0.0616)
Population Density	-0.0316** (0.0155)	-0.0268* (0.0143)	-0.0267* (0.0143)
$PM_{2.5}$	0.0001 (0.0008)	0.0002 (0.0008)	0.0002 (0.0008)
Ozone	0.0004 (0.0004)	0.0002 (0.0004)	0.0002 (0.0004)
HAP index	0.0026* (0.0014)	0.0021 (0.0014)	0.0021 (0.0014)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	4,653	4,653	4,653
R^2	0.914	0.915	0.915

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors in parentheses.



(a) (b)

Fig. 3 Spatial distribution of poverty-based Medicaid pressure changes and neighbor exposure. (a) Adjusted change in poverty-based Medicaid pressure (2015–2019 minus 2009–2014); treated counties outlined in bold black. (b) Neighbor exposure (WD) in the post period; treated counties outlined in bold white.

relative to controls. When the model includes the WD-only specification (col. 2), neighbor exposure is also positive and significant ($WD = 0.0142$, SE $= 0.0046$, $p < 0.01$), suggesting that counties with greater neighbor exposure experienced larger post-2015 increases.

Figure 3 is consistent with these estimates. Figure 3(a) maps the adjusted post–pre change in poverty-based Medicaid pressure and shows that increases are spatially concentrated around treated-county clusters and extend into nearby non-treated areas. Figure 3(b) maps neighbor exposure (WD), which is highest in and around the

treated clusters (North Central and Central Appalachia, with a smaller share in South Appalachia) and declines with distance. The Spatial-DID specification (col. 3) is most informative for distinguishing the two components. Once both D and WD are included, the estimated association is concentrated in neighbor exposure: WD remains positive and statistically significant, while D becomes small and statistically insignificant. This pattern suggests that the post-policy divergence is primarily associated with variation in neighbor exposure rather than an additional direct exposure.

6 Discussion

The evidence in this paper points to a simple but consequential conclusion: Medicaid pressure in Appalachia is not merely a county-level outcome, it is a regional process. The observed pattern is consistent with a landscape in which labor markets, health systems, and environmental exposures operate across county borders, generating clustered vulnerability and cross-county dependence that cannot be treated as statistical noise. In this setting, a "place-based" transition is only partially place-based in practice: households commute, relocate, and seek care across administrative lines, while economic decline and health risks diffuse through local networks. The substantive implication is that transition-related hardship should be conceptualized—and therefore governed—at a multi-county scale, rather than as a collection of isolated local trajectories.

Interpreting the covariate patterns reinforces a mechanism-based reading. The most robust correlates of higher Medicaid pressure are labor-market distress and weaker human capital, suggesting that the transition burden is channeled primarily through employment capacity and earnings prospects. Coal dependence, by contrast, does not present as a stable direct predictor once broader socio-economic conditions and spatial dependence are modelled. This does not imply that coal is irrelevant, rather, it indicates that coal exposure is likely to be mediated: its social consequences materialize through the labor-market and fiscal pathways that shape poverty and safety-net reliance. Moreover, the spillover structure highlights that what matters is not only how coal-reliant a county is, but also how the surrounding regional economy adjusts. Consistent with this interpretation, the spatial-DID results attribute the post-policy divergence primarily to neighbor exposure rather than a treated-only effect. This pattern is consistent with a diffusion mechanism: when post-policy shocks propagate through regional labor markets and service networks, the outcome is shaped less by whether a county is treated in isolation and more by its exposure to nearby treated areas. Where neighboring counties retain activity or fiscal capacity, they may partially buffer local vulnerability through commuting opportunities and service access; where neighboring counties experience labor-market deterioration, vulnerability propagates.

A similarly disciplined interpretation applies to environmental risks: once the surrounding exposure environment is accounted for, the remaining within-county association can reflect correlated structural features and residual variation rather than a literal protective effect. The more consistent signal is that exposure burdens and socioeconomic vulnerability co-move spatially, implying that environmental injustice

in Appalachia is embedded in a regional exposure–poverty structure rather than confined to individual "hotspot" counties. The policy-timed results around 2015 are best understood as corroborating a broader transition-era divergence rather than isolating a single-policy causal effect. The post-2015 widening between coal-reliant and non-coal counties is consistent with a period in which decarbonization commitments accelerated while coal decline continued, but the institutional context matters: state-level eligibility regimes and expansion status condition whether economic distress translates into enrolment, unmet need, or alternative coping strategies. This point also clarifies the paper's interpretive boundary. The outcome captures an income-linked pressure proxy rather than direct county-year Medicaid enrolment, so the strongest claim is about the economic and spatial foundations of safety-net reliance, not precise safety-net uptake. Taken together, the results support a just transition lesson that is often asserted but rarely demonstrated empirically: decarbonization can reallocate costs onto safety-net systems, and those costs travel through regional spillover channels. Policy design should therefore integrate labor-market stabilization with health-coverage planning at a regional scale—especially in the most vulnerable subregions—and future work should priorities direct county-level enrolment or utilization measures and explicit stratification by eligibility regimes to pin down the safety-net -burden channel more cleanly.

7 Robustness

Robustness to state-year shocks. Because Medicaid eligibility rules vary across states—particularly due to the optional adoption of PPACA Medicaid expansion—we re-estimate the spatial-DID model with state-by-year fixed effects to absorb statewide policy changes in each year. As shown in Appendix Table A.5, the main pattern is unchanged: neighbor exposure (WD) remains positive and statistically significant ($WD = 0.0126$), while direct exposure (D) remains insignificant. These results suggest that the post-2015 divergence is not primarily explained by unobserved state-year factors.

Robustness to spatial weights choices. To assess whether the neighbor-exposure (WD) result depends on how neighbors are defined, we re-estimate the spatial-DID model using alternative spatial weights matrices. Replacing Queen contiguity with Rook contiguity or using k-nearest-neighbor (kNN) weights ($k = 4, 6, 8$) yields a similar pattern (Appendix Table A.6). Across these alternatives, WD remains positive and statistically significant, whereas the direct term (D) remains insignificant. Overall, the evidence indicates that the main finding is not sensitive to a single specification of the spatial weights matrix W.

Robustness to treatment-cutoff choices. To assess whether the WD finding depends on the specific threshold used to define "coal-reliant" counties, we re-estimate the spatial-DID model under alternative pre-period coal-intensity cutoffs. Specifically, we redefine the treated group as counties in the top 10%, 20%, and 30% of baseline (2009–2014) coal intensity and consider a positive-support median cutoff to avoid the mass-at-zero issue in coal intensity (Appendix Table A.7). Across these alternatives, WD remains consistently positive and statistically significant, while D stays close to

zero and insignificant. Overall, the evidence indicates that the main finding is not an artifact of a single treatment cutoff.

Placebo cutoffs. To verify that the estimated effects are not an artifact of selecting 2015 as the breakpoint, we conduct placebo spatial-DID tests using only pre-policy years (2009–2014) and redefine the "post" indicator using alternative cutoffs (2011–2014). As shown in Appendix Table A.8, under each placebo cutoff both D and WD are statistically insignificant and close to zero. These placebo results support the interpretation that the main findings are not driven by mechanically splitting the sample at an arbitrary year and are consistent with using 2015 as the policy-period breakpoint.

8 Conclusion

This paper examines how Medicaid demand pressure evolved across Appalachian counties during the coal-to-clean transition from 2009 to 2019 and whether coal-reliant areas experienced differential changes after the 2015 clean power plan policy break-point. Because a consistent county–year Medicaid enrollment series is unavailable for the full period, we measure Medicaid demand pressure using "poverty-based Medicaid pressure" and validate this proxy using correlation analysis with existing Medicaid coverage data. We use a set of spatial and panel methods, paired with a Difference-in-Difference policy-period design, to distinguish local effects from neighbor exposure.

The results yield three main conclusions. First, poverty-based Medicaid pressure is strongly spatially clustered in Appalachia. Second, socioeconomic fundamentals—especially unemployment and education—are robust correlates of Medicaid pressure, and several spatially lagged covariances are statistically significant, indicating the importance of cross-county connection. Third, the policy-period analysis indicates a post-policy divergence between coal-reliant and non-coal counties. Importantly, the spatial-DID results suggest that the divergence is primarily associated with neighbor exposure, with little additional contribution from direct exposure. Robustness checks that absorb state-by-year shocks, vary the spatial weights matrix, multiple treatment cutoffs, and use placebo cutoffs support the stability of this pattern.

These findings carry a clear implication for "just transition" policy design. Transition-related hardship that manifests as pressure on the social safety net is not confined to coal-reliant counties alone; it appears to propagate through regional networks that cross county borders. As a result, policies that focus exclusively on coal counties may overlook nearby counties with high neighbor exposure that face similar post-transition pressures. Effective transition strategies should therefore integrate labor-market stabilization and economic diversification with health-coverage and safety-net planning at a regional scale, particularly in the most vulnerable Appalachian subregions, especially Central Appalachia.

This study also highlights several directions for future work. The outcome measure captures an income-linked pressure proxy rather than direct Medicaid enrollment, so extending the analysis with consistent utilization measures would help clarify program-specific burden channels. Future research should also explicitly stratify effects by

state eligibility regimes and Medicaid expansion status, and further test alternative definitions of spatial connectivity to better align spillover measurement with functional labor markets and healthcare access networks. Overall, by integrating geospatial modeling with a policy-period design, this paper provides a regional empirical framework for understanding how energy transitions can reshape safety-net pressures in resource-reliant communities.

Supplementary information. Not applicable.

Acknowledgements. Not applicable.

Declarations

- Funding. Not applicable.
- Conflict of interest/Competing interests. The authors declare that they have no competing interests.
- Ethics approval and consent to participate. Not applicable. The study uses secondary, publicly available, aggregated data and does not involve human participants.
- Consent for publication. Not applicable.
- Data availability. All data used in this study are publicly available. Coal production data are from the U.S. Energy Information Administration; socioeconomic indicators are from the Appalachian Regional Commission; and air quality and pollutant risk indicators are from the U.S. Centers for Disease Control and Prevention Environmental Public Health Tracking. Processed, analysis-ready datasets generated during the study are available from the corresponding author upon reasonable request (subject to file size and replication needs).
- Materials availability. Not applicable.
- Author contribution: G.S. and W.J. wrote the main manuscript text and G.S. prepared all the figures and tables. All authors reviewed the manuscript.

Appendix A

Table A.1 Poverty and Medicaid Coverage: Correlation (ACS 2015–2019)

Sample	Years	Corr (poverty rate, Medicaid coverage rate)	N (county-years)
All U.S. Counties	2015–2019	0.75	16,099
Appalachia Counties	2015–2019	0.62	2,115

Note: "Medicaid coverage rate" refers to the ACS Medicaid/means-tested public coverage rate.

Table A.2 County & Year FE Regression of Medicaid Coverage on Poverty (Dependent variable: Medicaid/means-tested public coverage rate)

	All U.S. Counties	Appalachia Counties
Poverty rate	0.248***	0.452***
	(0.033)	(0.085)
County fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	16,099	2,115
R^2	0.963	0.955

Notes: OLS with county and year fixed effects. Standard errors clustered by county in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.3 Global Moran's I on TWFE residuals by year (poverty) ($N = 423$ counties each year)

Year	Moran's I (TWFE residuals)	p (perm)
2009	0.0087	0.351
2010	0.1048***	0.001
2011	0.1572***	0.001
2012	0.1641***	0.001
2013	0.0689**	0.018
2014	0.0584**	0.030
2015	0.0262	0.191
2016	0.1265***	0.001
2017	0.1150***	0.001
2018	0.0998***	0.003
2019	0.1164***	0.001

Notes: Moran's I is computed on TWFE residuals from the baseline model with county and year fixed effects and controls. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.4 Model comparison for SAR-FE, SEM-FE, and SDM-FE

Model	LogLike	AIC	BIC	Pseudo R^2
SAR-FE	-7172	14380	14496	0.27
SEM-FE	-7177	14389	14499	0.26
SDM-FE	-7148	14338	14474	0.28

Table A.5 Robustness to state-year shocks

Model	Fixed Effects	D (Treat × Post)	WD (Neighbor Exposure)	N
#1	County + Year	0.0008 (0.0030)	0.0135** (0.0055)	4,653
#2	County + State×Year	0.0010 (0.0031)	0.0126* (0.0070)	4,653

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.6 Robustness to alternative spatial weights

W	D (Year FE)	WD (Year FE)
Queen	0.0008 (0.0030)	0.0135** (0.0055)
Rook	0.0010 (0.0030)	0.0130** (0.0055)
kNN $k = 4$	0.0026 (0.0029)	0.0101* (0.0053)
kNN $k = 6$	-0.0002 (0.0030)	0.0165*** (0.0059)
kNN $k = 8$	0.0008 (0.0030)	0.0156** (0.0063)

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.7 Robustness to alternative treatment thresholds

Threshold	D coef (SE)	D p-value	WD coef (SE)	WD p-value	N
top10	0.0030 (0.0047)	0.520265	0.0188 (0.0075)	0.012118**	4,653
top20	0.0006 (0.0031)	0.843571	0.0149 (0.0062)	0.017021**	4,653
top25	0.0008 (0.0030)	0.800966	0.0135 (0.0055)	0.013551**	4,653
top30	-0.0014 (0.0030)	0.653760	0.0127 (0.0048)	0.008046***	4,653
median	0.0015 (0.0035)	0.670745	0.0165 (0.0059)	0.004954***	4,653

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.8 Placebo cutoffs

Placebo cutoff	D coef (SE)	D p-value	WD coef (SE)	WD p-value	N
2011	-0.0015 (0.0025)	0.5638	-0.0029 (0.0034)	0.3929	2,538
2012	-0.0006 (0.0026)	0.8065	-0.0024 (0.0036)	0.4971	2,538
2013	-0.0000 (0.0026)	0.9909	0.0011 (0.0038)	0.7769	2,538
2014	0.0012 (0.0027)	0.6637	0.0022 (0.0038)	0.5530	2,538

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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